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AN EXAMINATION OF METHOD CONVERGENCE

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MEASUREMENT OF BUSINESS ECONOMIC PERFORMANCE: AN EXAMINATION OF METHOD CONVERGENCE

ABSTRACT

Strategic management researchers have measured business economic performance (BEP) through either perceptual assessments of senior executives or secondary data sources, but few explicitly evaluate the degree of convergence across methods. In an effort to examine method convergence, data were collected on three dimensions -- sales growth, net income growth, and profitability (ROI) using both methods. Although convergent and discriminant validity were achieved using the Campbell and Fiske's MultiTrait, MultiMethod (MTMM) framework and the Confiratory Factor Analysis (CFA) approach, they yielded different insights. The advantages of CFA over MTMM is demonstrated with implications for strategy research.

Business performance (or its broader notion of organizational effectiveness) is fundamental to management practice and research. Researchers have conceptualized and measured performance using many schemes -- depending upon their research questions, disciplinary focus, and data availability (for an overview, see Campbell, 1977; Chakravarthy, in press; Ford & Schellenberg, 1982; Hofer, 1983; Kanter & Brinkerhoff, 1981; Kirchoff, 1977; Seashore & Yuchtman, 1967; and Steers, 1975, 1977). Perhaps more than any other branch of organizational science, strategic management is centrally focused on issues of organizational performance (Schendel & Hofer, 1979). However, scant attention has been provided toward issues related to its measurement within this field. Organizational researchers generally focus on the overarching concept of organizational effectiveness (Campbell, 1977; Steers, 1975, 1977), but most strategy researchers have focused on a narrow domain, termed as business economic performance (BEP).

Although there are compelling reasons for viewing business performance in terms broader than BEP (Venkatraman & Ramanujam, 1986), the focus on BEP reflects our implicit acceptance of a goal-model or organization. Without getting into lengthy discussion on the conceptualization of performance, we assume the individual researchers have justifiable arguments for conceptualizing performance in terms of BEP. Thus, by focusing on the measurement of BEP, we seek to (a) develop a scheme for classifying alternative approaches to measuring BEP; and (b) examine the degree of convergence of two different measurement schemes using two different data-analytic frameworks, i.e., the MultiTrait, MultiMethod (MTMM) and the confirmatory factor analysis (CFA).

MEASUREMENT OF BEP: A CLASSIFICATORY SCHEME

Two major issues underlie the measurement of BEP. One is the data source--which could be either primary (e.g., data collected directly from the target organization), or secondary (e.g., data collected from sources external to the target organization). The other issue is the mode of performance assessment--which could either be "objective" (e.g., based on some established system such as internal accounting, or systematic tracking by external agencies) or "perceptual" (e.g., judgments made by executives). Based on these two issues, a two-dimensional four-cell classificatory scheme for the measurement of BEP is developed in Figure 1, which is self-explanatory.

Insert Figure 1 about here

The four cells highlight different approaches to the measurement of BEP. It is important to recognize that no cell is intrinsically superior to the others in terms of consistently providing valid and reliable performance measurement. While measurements based on secondary data sources permit replication, they may not always be accurate (see especially, Rosenberg & Houglet, 1974; San Miguel, 1977). The primary method, on the other hand, may introduce method bias (Huber & Power, 1985) due to hierarchy, knowledge, etc., but may not permit replicability. Similarly, while objective assessment may reduce the possibility of overrating performance, they may not always be available in the form desired for the specific research question (e.g., in comparison with competitors, or in relation to the goals). The perceptual assessment, permits one to obtain data in the required format, but involves the respondents to make complex and difficult judgements (Phillips, 1981).

THE STUDY

Overview

Given that each approach may have questionable measurement properties, it is important to examine "method convergence" (Campbell & Fiske, 1959) to ensure that the variance reflected is that of trait and not of method. Towards this end, the following two methods are used: perceptual data from company executives (Cell 3), and secondary objective data from external sources (Cell 2). According to Bouchard, convergence between different approaches "enhances our belief that the results are valid and not a methodological artifact" (1976; p. 268). When maximally differing methods are used, the approach is termed "between-methods" triangulation (Denzin, 1978; Jick, 1979), which rests on the assumption that the two methods do not share the same weakness or potential bias (Rohner, 1977).

A recent study by Dess and Robinson (1984), using self-reported "objective" data and subjective assessments of two performance indicators--return on assets and sales growth--reported a close correspondence between them. Their two approaches (representing Cells 1 and 3 respectively) are conceptually similar since they employ data collected from only primary source. Such approaches represent "within-method" type of triangulation, and as noted by Denzin, "Observers delude themselves into believing that ...different variations of the same method generate...distinct varieties of triangulated data. But the flaws that arise using one method remain..." (1978, pp. 301-302).

In contrast, the present study, moves the measurement of BEP toward the "between-methods" triangulation, which "allows researchers to be more confident of their results" (Jick, 1979; p. 608). Since the two approaches differ along both dimensions of the classification scheme, (Figure 1), we argued that the level of common method bias is minimal.

Measurements of BEP

Dimensions of BEP. Three dimensions-- sales growth, net income growth, and return on investment (ROI)--were chosen to reflect BEP. Two reasons guided our choice. One, in a review of performance dimensions typically used by different disciplines, Hofer (1983) noted that these are the most common measures in strategy research. Two, they closely correspond to the key dimensions of performance distilled by Woo and Willard (1983) based on their analysis of PIMS data--viz., (i) profitability; (ii) relative market position; (iii) change in profitability; and (iv) growth in sales and market share.

Perceptual Primary Measures. For each of the three indicators, managers were requested to indicate their position, not of absolute performance but relative to their major competitors. A five-point interval scale ranging from -2 (much worse than competition) to +2 (much better than competition) with the neutral point 0, indicating a level of performance equal to that of competition, was employed. Data were collected from senior-level managers (presidents, vice presidents of functional areas or vice presidents of corporate planning) as a part of a larger project during February-May 1984 (see Ramanujam, Venkatraman & Camillus, 1986 for details). Although the larger project had a response rate of over 33% (207 out of 600), only 86 cases are used in this study. Since anonymity was guaranteed, the respondent's name and affiliation was voluntary. 86 respondents indicated their organizational affiliations which was necessary to collect corresponding performance data from secondary sources.

Objective Secondary Measures. For each of the three indicators, objective secondary measures were assembled from the Business Week magazine's "Inflation Scorecard" for the year 1983, as reported in the March 21, 1984, issue (compiled from the Standard & Poor's COMPUSTAT® tapes). Relative performance was operationalized as "firm performance relative to industry"

--where industry referred to the principal SIC industry classification in which the firm was normally placed. It was measured as the difference between the value of the indicator for the firm and the industry. For example, relative sales growth was the sales growth of the focal firm minus the sales growth of its primary industry.

Examining Convergence Using the MTMM Framework

Table 1 presents descriptive statistics as well as the MTMM matrix, where the entries are Pearson's zero-order correlations. The first of the four criteria for analyzing an MTMM matrix refers to convergent validity, which requires that all the diagonal coefficients in the lower left quadrant of the matrix (termed "validity coefficients") be "sufficiently large" and statistically significant (Campbell & Fiske, 1959). In Table 1, all the three validity coefficients are greater than 0.4, $p < .01$.

Insert Table 1 about here

The other three criteria relate to discriminant validity, namely, whether the three traits are different from one another or not. The second criterion requires that each validity coefficient should be larger than the "different trait- different method" correlations (which are in the same row or column as the validity coefficients). As shown in Table 1, this condition is satisfied in <u>all</u> three cases. The third criterion requires that each validity coefficient should be larger than the "different trait-same method" (which involve the same variable as that of the validity coefficient in the lower right and upper left quadrants). This is satisfied in two of the four cases for the sales growth measure, in one out of the four cases for the profit growth measure, and in three out of the four cases for the profitability measure. The general support for this criterion appears to be "moderate."

The final criterion requires that the pattern of correlations in each of the four triangles (both solid and dashed) in the matrix should be similar. A test of this similarity can be accomplished by ranking the correlations in each tringle and deriving a measure of the rank correlation across the triangles. A Friedman two-way test was conducted for this purpose. Its associated χ^2 statistic was 6.50 (df=2), not statistically significant at a p value $< .01$, but approaches statistical significance at $p < .05$. Thus, we could conclude that the relative rankings of the correlations are preserved within the four triangles using the more stringent level of statistical significance or conclude the opposite based on a less stringent level.

Thus, although one can conclude that the requirements of convergent and discriminant validities are broadly satisfied, it is evident that the various criteria are open to researchers' interpretation. Indeed, it has been shown that studies which satisfied the broad MTMM criteria failed to turn up similar results when the variance in measurement was partitioned into its constituent components (see Bagozzi, 1980, pp. 136-153 for a detailed discussion). Consequently, complementary assessments using the CFA approach is attempted, which can also be used to evaluate if the methods are equally efficient for measuring the three triats (which cannot be directly obtained from the MTMM analysis).

Examining Convergence Using the CFA

The CFA framework (Jöreskog, 1969; Jöreskog & Sörbom, 1978) has been employed to test a variety of measurement models in disciplines such as psychology, sociology, and marketing (Bagozzi, 1980; Fornell, 1982), as well as strategic management (Farh, Hoffman & Hegarty, 1984; Venkatraman, 1985). Specifically, the use of this framework provides: (a) a formal statistic for

judging the entire validity of a construct; (b) an indication of the degree to which operationalizations measure the concepts they intend to measure; and (c) a decomposition of the measurement variance into its constituent components. A brief technical appendix is provided to serve as an overview, and those requiring detailed treatments are directed to Bagozzi (1980), Bagozzi & Phillips (1982), Fornell (1982), Jöreskog & Sörbom (1978; 1979), and Long (1983).

The required analysis are conducted using a set of three interrelated models (Bagozzi & Phillips, 1982). The first is a test for convergent validity with only the trait factors. If the first model is not supported, then it is extended by adding method factors to evaluate whether the additional incorporation of systematic sources of variation provides better support to the second model. The third model tests for discriminant validity, i.e., that the three dimensions of BEP are dissimilar. All the model parameters estimated using the LISREL IV program (Jöreskog & Sörbom, 1978).

Testing for Convergent Validity--Model 1. Convergent validity refers to the degree to which two or more attempts to measure the same trait through maximally different methods are in agreement. This model hypothesizes that all the variation and covariation in the measurement can be accounted for by the traits that the measurements are intended to capture plus random error. Figure 2 is a diagramatic representation of such a model, where three dimensions of BEP are each measured by two methods. For example, sales growth is measured by X_1 (primary method) and X_2 (secondary method). The results of LISREL IV analysis for this model yielded a χ^2 (df:6) value of 54.37; $p < 0.01$. The implication is that the underlying hypothesis that all variations are due to underlying trait and random error only should be rejected.

Insert Figure 2 here

Testing for Convergent Validity with Method Factors--Model 2. Since the previous model failed to achieve a satisfactory fit to the data, one can examine potential improvement with explicit modeling of method factors -- "primary" and "secondary" sources of data. The rationale is that the observations are not only a function of the trait and random error, but are also influenced by systematic sources of variation such as the method of collecting data. Two method factors are added to the first model as systematic sources of variation. A diagramatic representation of the second model with its estimates are provided in Figure 3.

Figure 3 about here

The analysis of the second model yielded a χ^2(df:2) of 1.97; $p < .37$, and the difference in χ^2 between the first and the second model was 52.4 (df:4), significant at $p < 0.01$. Further, Δ index of 0.99 indicated that more than 99% of the measure variation is captured by the model. As an alternative to Δ, which is based on a relatively weak rival hypothesis of mutual independence, a modified null index $\bar{\Delta}$, based on the base model of six-indicator, one construct performance model was calculated. This is in line with Bentler and Bonett's (1980) suggestion "that the most restrictive, theoretically defensible model should be used in the denominator". $\bar{\Delta}$ was .97.

The individual λ parameters (λ_1 to λ_6) connecting the observations to the underlying traits are all statistically significant given by their strong t-values. Similarly the relationships among the performance dimensions are as expected; the association between sales growth and profit growth as well as profitability and profit growth are positive and significant, while profitability and sales growth are not significantly related. These results provide strong support to the second model and the underlying

hypothesis that measures achieve convergent validity only when the method factors (i.e., sources of systematic variation) are explicitly incorporated into the model.

Testing for Discriminant Validity--Model 3. This will be achieved when the correlations between the traits are significantly lower than unity. This requires a comparison of the model in Figure 3 with a similar model in which the three correlations are constrained to equal unity. A significantly lower χ^2 value for the model with the correlations unconstrained provides support for discriminant validity. A χ^2 difference value (χ^2_d) value with an associated p value less than 0.05 (Jöreskog, 1971) supports this criterion.

The model statistic for the constrained model is: $\chi^2(df:5) = 20.21$, and the χ^2_d statistic is 20.21, $p < .01$. This satisfies the criterion for discriminant validity (Jöreskog, 1971). However, the analysis of model 2 indicated that ϕ_{32} was large (0.724), which could imply that dimensions 2 and 3 may be sub-dimensions of a broader construct. In order to rule out this rival interpretation, a separate model was estimated, with ϕ_{32} constrained to 1.0. Since the χ^2_d statistic is 5.66, $p < .05$, the results support discriminant validity of the three dimensions of BEP.

Based on the analysis reported in Figure 3, we decomposed the variance into trait, method and error components, and calculated the measure reliability (Werts, Linn & Joreskog, 1971). This is summarized in Table 2.

Insert Table 2 about here

DISCUSSION

Conceptualization and measurement of business economic performance is an important and challenging task facing strategy researchers today. This issue, although primarily important for research purposes, has important implications

for managerial practice. This is because the results of empirical strategy research used for developing managerial prescriptions could be suspect if measurement quality has not been established. Thus, managers should not overly rely on those results where scant attention is provided at addressing important measurement issues.

In addressing such an issue, this study specifically sought to examine convergence between two maximally different approaches to measuring BEP. Results of the MTMM analysis and the CFA indicate that there is a strong degree of convergence between the two methods. The implications for future research on the measurement of BEP are discussed below.

Managerial Assessments of Performance

There exists a general belief that the use of an "informant approach" -- where key managers are asked to provide information on organizational properties, may not be valid since managers are likely to overrate their performance. In the absence of serious research attention, this issue has largely remained an untested proposition. This study provided modest support in establishing that managers tend to be less biased in their assessments of their organizational performance than researchers have tended to give them credit for. It appears that perceptual data from senior managers, which tend to strongly correlate with the secondary data (Table 1), can be employed as acceptable operationalizations of BEP.

The use of single informant per unit of analysis to collect data on organization-level performance constructs limits our ability to rule out the possibility of functional or response bias (Huber & Power, 1985; Phillips, 1981). Since respondents in our study were senior-level managers (e.g., vice president-strategic planning, president, or functional vice president) who are key members of the firm, one can argue that they are "representatives" of the organization. Nevertheless, as noted by Venkatraman and Grant (1986) the need

to employ multiple respondents to measure organizational-level constructs such as BEP can not be dismissed by strategy researchers. A useful line of extension is to examine if systematic differences exist between managers based on factors such as hierarchy, or functions.

Insights From the CFA Approach

An important methodological contribution of this study is the comparison of the relative benefits of the CFA approach over the traditional MTMM-type analysis for strategy research (see Table 3). The analysis based on the MTMM matrix provided support for the convergent validity hypothesis but the support for the discriminant validity was rather ambiguous and open to different interpretations (see Table 1). In contrast, the CFA approach enabled us to model the measurement variance using three important components -- trait, method, and random error, and the results (Figure 3) indicated that more than 99% of the measurement variance could be so modelled.

Insert Table 3 About Here

In addition, by treating the data from the two methods as imperfect measurements of the unobservable BEP construct, and decomposing the measurement variance, the relative superiority of the methods is evaluated. Based on Table 2(a), we can conclude that the data from the primary method is more reliable than the data from the secondary method for sales growth with its trait variance explaining 62.7% of the overall measurement variance as opposed to 24% for the secondardy method. In contrast, for the profitability dimension of BEP, the secondary method appears to be a little more reliable (0.562) than the primary method (0.452). Both appear to be poor measures for operationalizing net income growth.

The CFA results are to be interpreted with some caution. Although the sample size (an average of 80, after accounting for some missing data)

satisfies the generally accepted minimum size (Bagozzi, 1980; Lawley & Maxwell, 1971), the chi-squared statistic is sensitive to sample size (Bearden, Sharma, & Teel, 1982). Hence, we relied on the difference in chi-square (χ^2_d) statistics in the sense of assessing a set of nested models (which is less sensitive to sample size), the Δ index (Bentler & Bonett, 1980) which is independent of sample size, and a modified null index (Δ) based on a more plausible rival hypothesis. Thus, although, we attempted to reduce estimation problems arising from the relatively small sample size, a useful extension will be to replicate this study and test these results using a larger sample set.

Overall, our findings seem to question Dess and Robinson's claim that objective measures are generally preferred, and that perceptual evaluations are good substitutes for objective data whenever "(1) accurate objective measures are unavailable, and (2) the alternative is to remove the consideration of performance from the research design" (1984, p. 271). Based on our results, we would caution against treating any one particular method of measuring BEP (or any other construct) as being universally superior. Hopefully, the application of confirmatory factor analysis to the problem addressed here would stimulate other strategy researchers to employ such an analytical scheme to explicitly test the important issue of method superiority.

REFERENCES

Anderson, J. C. & Gerbing, D. W. (1984). The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. Psychometrika, 49, 155-173.

Bagozzi, R.P. (1980) Causal models in marketing, N.Y.: Wiley.

Bagozzi, R.P. (1981) An examination of the validity of two models of attitude. Multivariate Behavioral Research, 16, 323-359.

Bagozzi, R.P., & Phillips, L.W. (1982) Representing and testing organizational theories: A holistic construal. Administrative Science Quarterly, 27, 459-489.

Bearden, W.O., Sharma, S., & Teel, J.H. (1982) Sample size effects on chi-square and other statistics used in evaluating causal models. Journal of Marketing Research, 19, 425-430.

Bentler, P.M., & Bonett, D.G. (1980) Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88, 588-606.

Bouchard, T.J., Jr. (1976) Unobtrusive measures: An inventory of uses. Sociological Methods and Research, 4, 267-300.

Campbell, D.T., & Fiske, D.W. (1959) Convergent and discriminant validation by the multitrait-multimethod matrix. Psychological Bulletin, 56, 81-105.

Campbell, J.P. (1977) On the nature of organizational effectiveness. In Goodman, P.S., Pennings, J.M. & Associates. New perspectives on organizational effectiveness. San Francisco: Jossey-Bass., pp. 13-55.

Chakravarthy, B.S. (1986) Measuring strategic performance. Strategic Management Journal, in press.

Denzin, N.K. (1978) The research act. 2nd Ed., New York: McGraw-Hill.

Dess, G.G., & Robinson, R.B. (1984) Measuring organizational performance in the absence of objective measures: The case of the privately-held firm and conglomerate business unit. Strategic Management Journal, 5, 265-273.

Farh, J.L., Hoffman, R.C., & Hegarty, W.H. (1984) Assessing environmental scanning at the subunit level: A multitrait multimethod analysis. Decision Sciences, 15, 197-220.

Ford, J.D., & Schellenberg, D.A. (1982) Conceptual issues of linkage in the assessment of organizational performance. Academy of Management Review, 7, 49-58.

Fornell, C. (Ed.) (1982) A second generation of multivariate analysis. N.Y.: Praeger.

Fornell, C., & Larcker, D. F. (1981) Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research, 18, 39-50.

Fredrickson, J.W., & Mitchell, T.R. (1984) Strategic decision processes: Comprehensiveness and performance in an industry with an unstable environment. Academy of Management Journal, 27, 399-423.

Hofer, C.W. (1983) ROVA: A new measure for assessing organizational performance. In R. Lamb (Ed.), Advances in strategic management, Vol. 2, 43-55. New York: JAI Press.

Huber, G., & Power, D. (1985) Retrospective reports of strategic-level managers. Strategic Management Journal, 6, 171-180.

Jick, T.D. (1979) Mixing qualitative and quantitative methods: Triangulation in action. Administrative Science Quarterly, 24, 602-611.

Jöreskog, K.G. (1971) Statistical analysis of congeneric tests. Psychometrika, 36, 109-133.

Jöreskog, K.G. (1979) "Authors addendum to: A general approach to confirmatory maximum likelihood factor analysis", pp. 40-43 in K. G. Jöreskog and D. Sörbom (Eds.). Advances in factor analysis and structural equation models. Cambridge, Mass: Abt Books.

Jöreskog, K.G., & Sörbom, D. (1978) Analysis of linear structural relationships by method of maximum likelihood. Chicago, IL: National Educational Resources.

Jöreskog, K.G., & Sörbom, D. (1979) Advances in factor analysis and structural equation models. Mass.: Abt Books.

Kanter, R.M., & Brinkerhoff, D. (1981) Organizational performance: Recent developments in measurement. Annual Review of Sociology, 7, 322-349.

Kirchoff, B. (1977) Organization effectiveness measurement and policy research. Academy of Management Review, 2, 347-355.

Lawley, D.N., & Maxwell, A.E. (1971) Factor analysis as a statistical method. London: Butterworth.

Long, J.S. (1983) Confirmatory factor analysis. Sage University Paper Series on Quantitative Application in the Social Sciences, 07-033. Beverly Hills and London: Sage Publications.

Phillips, L.W. (1981) Assessing measurement error in key informant reports: A methodological note on organizational analysis in marketing. Journal of Marketing Research, 5, 395-415.

Ramanujam, V., Venkatraman, N., & Camillus, J. C. (1986) Multi-objective assessment of the effectiveness of strategic planning: A discriminant analysis approach. Academy of Management Journal, 26, 347-372.

Rindskopf, D. (1983) Parametrizing inequality constraints on unique variances in linear structural models. Psychometrika, 48, 73-83.

Rohner, R.P. (1977) Advantages of the comparative method of anthropology. Behavioral Science Research, 12, 117-144.

Rosenberg, B., & Houglet, M. (1974) Error rates in CRSP and COMPUSTAT databases and their implications. Journal of Finance, 1303-1310.

San Miguel, J. G. (1977) The reliability of R&D data in COMPUSTAT and 10-K reports. The Accounting Review, 52, 638-641.

Schendel, D.E., & Hofer, C.W. (Eds.) (1979) Strategic management: A new view of business policy and planning. Boston: Little, Brown.

Seashore, S.E., & Huchtman, E. (1967) Factoral analysis of organizational performance. Administrative Science Quarterly, 12, 377-395.

Sobel, M. E., & Bohrnstedt, G. W. (1985) Use of null models in evaluating the fit of covariance structure models. In Nancy B. Tuma (Ed.). Sociological Methodology - 1985, San Francisco: Jossey-Bass, pp. 152-178.

Steers, R. (1975) Problems in measurement of organizational effectiveness. Administrative Science Quarterly, 20, 546-558.

Steers, R. (1977) Organizational effectiveness: A behavioral view. The Goodyear series in management and organizations. Santa Monica, CA: Goodyear.

Venkatraman, N. (1985) Strategic orientation of business enterprises: The construct and its measurement. Unpublished Doctoral Dissertation, University of Pittsburgh.

Venkatraman, N., & Grant, J.H. (1986) Construct measurement in organizational strategy research: A critique and proposal. Academy of Management Review, 11, 71-87.

Venkatraman, N., & Ramanujam, V. (1986) Measurement of business performance in strategy research: A comparison of approaches. Academy of Management Review, 11 (October), in press.

Werts, C.E., Linn, R.N., & Jöreskog, K.G. (1974) Interclass reliability estimates: Testing structural assumptions. Educational and Psychological Measurement, 34, 25-33.

Woo, C.Y., & Willard, G. (August, 1983) Performance representation in strategic management research: Discussions and recommendations. Paper presented at the Academy of Management Meeting at Dallas.

FIGURE 1

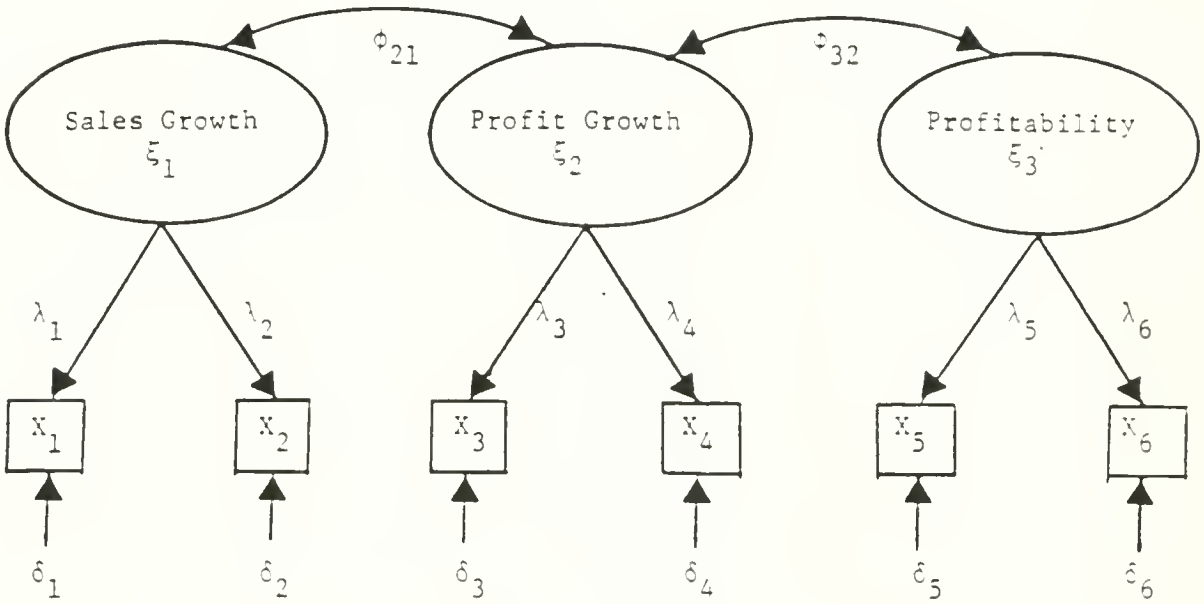
MEASUREMENT OF BUSINESS ECONOMIC PERFORMANCE:

A CLASSIFICATORY SCHEME

MODE OF ASSESSMENT	SOURCE OF DATA: PRIMARY (Directly from the organization)	SOURCE OF DATA: SECONDARY (From Sources External to the organization)
"Objective" (say, based on records/ systems)	"Factual" reports of Business Performance e.g., Internal Management Accounting records, MIS reports, Indices in PIMS Project (e.g., ROI) 1	"Reports Compiled by and for External Agencies" e.g., Annual Reports, 10K Reports, Business Week Scorecard 2
"Perceptual" (judgments)	3 Perceptual Assessments and evaluations by managers; some indices in PIMS project (e.g., relative market share position)	4 Perceptual assessments of performance by industry observers/ other "experts" external to organization

FIGURE 2

A MODEL OF CONVERGENT VALIDITY WITH ONLY TRAIT FACTORS[a]



χ^2(df:6) = 54.37; p $\simeq$ .00

Δ = 0.72

$\overline{\Delta}$ = 0.27

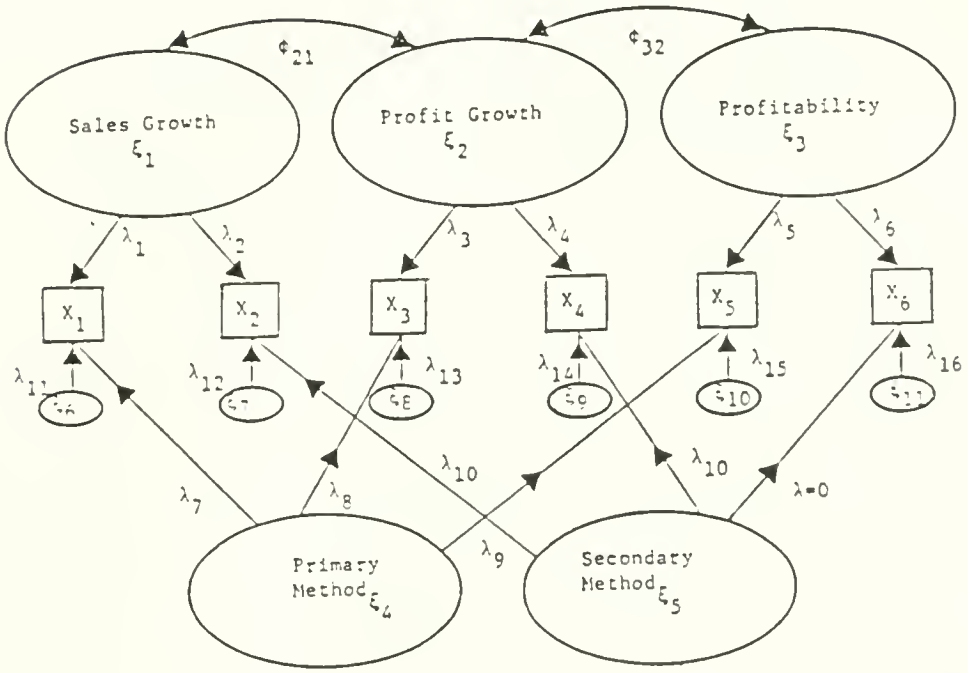
Parameter	ML Estimate	t-value	Parameter	ML Estimate	t-Value
λ_1	.719	5.49	ϕ_{21}	.792	6.13
λ_2	.615	4.86	ϕ_{32}	.888	8.30
λ_3	.809	7.30	ϕ_{31}	.420	3.13
λ_4	.524	4.69	θ_{δ_1}	.483	3.25
λ_5	.973	8.36	θ_{δ_2}	.622	4.59
λ_6	.528	4.64	θ_{δ_3}	.345	3.04
			θ_{δ_4}	.725	5.91
			θ_{δ_5}	.054	0.33
			θ_{δ_6}	.721	5.80

ϕ_{31} not drawn for schematic clarity.

[a]The notations of structural equation modeling are followed. Latent (unobservable) variables or theoretical constructs are drawn as ellipses; observable indicators are presented as squares; measurement relations are shown as arrows; error factors are also represented as arrows but without origin; and parameters to be estimated are depicted as Greek letters, corresponding to the notations in the technical appendix.

FIGURE 3

A MODEL OF CONVERGENT VALIDITY WITH TRAIT AND METHOD FACTORS



Parameter	ML Estimate	t-value[a]
λ_1	0.792	2.64
λ_2	0.490	2.71
λ_3	0.645	4.50
λ_4	0.604	4.23
λ_5	0.672	4.23
λ_6	0.750	5.19
λ_7	0.284	1.74
λ_8	0.548	2.05
λ_9	0.733	2.40
λ_{10}	0.712	7.40
λ_{11}	0.517	1.32
λ_{12}	0.484	4.15
λ_{13}	0.516	2.58
λ_{14}	0.353	2.70
λ_{15}	0.000	0.00
λ_{16}	0.661	4.93
ϕ_{21}	0.577	4.10
ϕ_{31}	0.232	1.30
ϕ_{32}	0.724	6.65

ϕ_{31} not drawn for schematic clarity.

Model Statistics: Summary

χ(df:2) = 1.97
p = 0.37
$\hat{\Delta}$ = 0.99
$\hat{\rho}$ = 0.97

[a]A t-value greater than 1.96 is statistically significant at p-levels better than .05.

TABLE 1

CONVERGENCE OF OPERATIONALIZATIONS OF

BUSINESS ECONOMIC PERFORMANCE: AN MTMM ANALYSIS

			PRIMARY			SECONDARY			DESCRIPTIVE STATISTICS	
			SG[a]	PG	ROI	SG	PG	ROI	MEAN[b]	SD
Primary and Perceptual (Cell 3)	x_1	SG	1.00						3.32	0.91
	x_3	PG	0.47	1.00					3.47	1.05
	x_5	ROI	0.36	0.74	1.00				3.24	1.06
Secondary and Objective (Cell 2)	x_2	SG	0.44	0.24	0.15	1.00			1.13	12.54
	x_4	PG	0.32	0.42	0.33	0.69	1.00		(-)2.64	21.71
	x_6	ROI	0.10	0.36	0.51	0.02	0.28	1.00	(-)0.54	9.96

Convergent Validity: Criterion 1

All validity coefficients (SG: 0.44; PG: 0.42; ROI: 0.51) are statistically significant at $p < 0.01$.

Discriminant Validity: Criteria 2 and 3

Validity Coefficient	Criterion 2 % Satisfied	Criterion 3 % Satisfied
0.44	100	50
0.42	100	25
0.51	100	75

Criterion 4

Chi-squared statistic for Friedman's non-parametric test for the rankings of the correlations within the four triangles: 6.50 (df=2), not statistically significant at $p < .01$.

a) SG: Sales Growth; PG: Profit (net income) growth; ROI: Return on Investment. Entries in the matrix are Pearson's zero-order correlations.

b) Primary data are based on five-point Likert-type scale, secondary data are actual values.

TABLE 2

PARTITIONING OF VARIANCE AND MEASURE RELIABILITY

BASED ON RESULTS OF CONFIRMATORY FACTOR ANALYSIS

(a) VARIANCE-PARTIONING: INDIVIDUAL-INDICATOR ANALYSIS

DIMENSIONS	INDICATORS	VARIANCE COMPONENTS		
		Trait[a]	Method	Random Error
Sales	X_1	0.627	0.080	0.267
Growth	X_2	0.240	0.507	0.234
Net Income	X_3	0.416	0.300	0.266
Growth	X_4	0.365	0.507	0.234
Profitability	X_5	0.452	0.537	0.000
	X_6	0.562	0.000	0.437

[a]This can also be interpreted as the reliability (p_i) of the observed indicators based on Werts, Linn, and Joreskog (1974) that $\rho_i = \lambda_i^2$ Var(A)/{λ_i^2 Var(A) + Σ Error (method & random) variance}

(b) VARIANCE - PARTITIONING: A SUMMARY

Variance Components \ Methods	Primary	Secondary
Trait	49.83%	38.9%
Method	30.56%	33.8%
Random Error	17.76%	26.53%

Table 3

MTMM and CFA Approaches: A Comparison of Research Insights In this Study

Research Questions	MTMM Analysis	Confirmatory Factor Analysis
1. Assessment of Convergence in Measurements Across Two Methods	Based on a statistical test that tests the hypothesis H_0: r = 0; H_a: r > 0.	Based on an analysis that models variance in measurement into three components and obtaining a goodness-of-fit statistics that indicates the degree of fit between the observed covariance matrix and the model-fitted covariance matrix.
2. Assessment of Discriminant Validity	Based on a set of three criteria regarding the pattern of correlations in the different "triangles" of the matrix; critiera are rather loose and open to researcher interpretations.	Test statistic based on difference in model statistics due to relaxation of constraints that the dimensions are perfectly collinear.
3. Examining relative superiority of the methods in measuring the different traits.	Not directly possible.	Possible through variance - partitioning anlysis.

TECHNICAL APPENDIX

An overview of the model specification and identification based on the confirmatory factor analytic approach is presented here.

I. Specification of Model I. Following Jöreskog's work, the basic model for convergent validity can be written as:

$$X = \Lambda\xi + \delta \qquad (1)$$

where

X is a vector of p measurements,
ξ is a $k < p$ vector of traits,
δ is a vector of unique scores (random errors), and
Λ is a p x k matrix of factor loadings.

With the assumptions of $E(\xi) = 0$, $E(\xi\xi') = \Phi$, and $E(\delta\delta') = \Psi$, the variance-covariance matrix of X can be written as

$$\Sigma = \Lambda\phi\Lambda' + \Psi \qquad (2)$$

where

Σ is the variance-covariance matrix of observations,
ϕ is the intercorrelation among the traits, and
Ψ is a diagonal matrix of error variances (θ_δ) for the measures.

Maximum likelihood parameter estimates for Λ, ϕ, Ψ, and a χ^2 goodness of fit index for the null model implied by equations (1) and(2) can be obtained from the LISREL program (Jöreskog & Sörbom, 1978). The probability level associated with a given χ^2 statistic indicates the probability of attaining a larger χ^2value, given that the hypothesized model holds. The higher the value of p, the better is the fit, and as a rule of thumb, values of $p > 0.10$ are considered as indications of satisfactory fit (Lawley & Maxwell, 1971).

However, sole reliance on the χ^2statistic is criticized for many reasons (Fornell & Larcker, 1981), and researchers increasingly complement this statistic with additional statistics. A commonly used statistic is Bentler and Bonett's (1980) incremental fit index Δ -- which is an indication of the practical significance of the model in explaining the data. The Δ index is represented as:

$$\Delta = (F_0 - F_K)/F_0 \qquad (3)$$

where

F_0 = chi-square value obtained from a null model specifying mutual independence among the indicators, and

F_K = chi-square value for the specified theoretical model.

Since this index is often criticized for its weak base model (Sobel & Bohrnstedt, 1985), another index Δ based on the base model that the six indicators represent one underlying performance construct was also used.

II. Specification of Model II. The estimation of this model along the lines of the specification of Model I yielded improper solutions, specifically a negative error variance which is unacceptable. As noted by Anderson and Gerbing (1984), "two indicators per factor models were problematic for obtaining a convergent and proper solution" (p. 171). A common approach to this problem is to fix such offending variance estimates at zero which is questionable given its likely impact on the estimates of other parameters. A solution to this problem, termed as the Heywood case in factor analysis, is suggested by Rindskopf (1983). Without any violation of the assumptions of the confirmatory factor model, the equation (2) can be respecified as:

$$\Sigma = \Lambda \phi \Lambda' \qquad (4)$$

where Λ becomes a 6 x 11 matrix, and Φ is a (11 x 11) symmetric matrix with the diagonals fixed at unity. The diagramatic representation in Figure 3 follows Rindskopf's specification and the model estimates are provided accordingly. [λ^2_{11} through λ^2_{16} indicate the error variances].

III. Model Identification. A necessary condition for model identification is positive degrees of freedom (i.e., the number of distinct variances and covariances in Σ less the number of free parameters to be estimated). In addition, Joreskog (1979) noted the following sufficient conditions for uniqueness of parameter estimates:

(1) Φ must be a symmetric positive definite matrix with ones in the diagonal

(2) Λ must have k - 1 fixed zeroes in each column

(3) Λ_s must have a rank equal k - 1, where Λ_s for

s = 1,2,...,**k** is the submatrix of Λ comprised of those rows with fixed zeroes in the sth column.

Where **k** = number of unobservable latent traits.

Both the necessary and sufficient conditions are satisfied in the case of the first model (Figure 2).

The second model introduces six more parameters (due to method factors) which violates the necessary and sufficient conditions. Consequently a set of constraints have to be imposed based on theoretical and/or empirical considerations.

A variety of models with varying constraints were evaluated and we finally decided to impose just one theoretical constraint, namely that the impact of the secondary method on the indicators x_2, x_4, and x_6 would be equal. However, it provided a negative λ for the parameter linking this method to x_6 and was not significantly different zero. Thus, based on this empirical consideration, this λ was fixed at zero. Figure 3 reflects this model. [Since the correlation matrix is provided in Table 1, readers wishing to examine alternative model specifications have an opportunity to do so.]

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